represent (M by M) positive definite matrixes, C an (M by N) matrix, D an (N by N) positive definite matrix, an inverse matrix of A is given by

$$A^{-1}=B-BC(D+C^{H}BBC)^{-1}C^{H}B \qquad (33)$$

Applying this Lemma to the calculation of the inverse matrix in Eq. (32),

$$H_L(n)H_L^{H}(n)+\sigma^2 I=B^{-1}+CD^{-1}C^{H},$$

$$H_L(n)H_L^{H}(n)=CD^{-1}C^{H},$$

$$\sigma^2 I=B^{-1},$$

$$h(n)=C,$$

$$D^{-1}=I,$$

$$H_L^{H}(n)=C^{H}$$

By using them to calculate Eq. (33), the inverse matrix calculation in Eq. (32) is solved. Incidentally, Eq. (33) also contains an inverse matrix calculation $(D+C^{H}BBC)^{-1}$, but this inverse matrix is also scalar, and hence it can similarly be calculated.

The thus calculated tap coefficient value **G**(n) is used to perform linear filtering of the difference value $\mathbf{R}_c(n)$ by the transversal filter 111, and the filtering result **Z**(n) and the estimated channel impulse response value $\mathbf{H}_L(n)$ stored in the storage part 106B are used to calculate Eq. (25) in the soft decision value calculating part 120 to derive the soft decision value $\Lambda_1[b(n)]$. The equivalent amplitude $\mu(n)$ in Eq. (25) is given by the following equation by substituting Eq. (31) for $\Lambda(n)$ in ~~Fig.~~ Eq. (23). Eq. 23 on page 8, lines 10-11

$$\mu(n)=[H_L(n)^{H}[H_L(n)H_L(n)^{H}+\sigma^2 I]^{-1}H_L(n)]$$

$$=H_L(n)^{H}G(n) \qquad (34)$$

Incidentally, in the first iteration of equalization the tap coefficient calculating part 112 of the linear filter part 110 may also use the Matrix Inversion Lemma to calculate the tap coefficient **G**(n).

As described above, this embodiment permits reduction of the

number M needs to be at least 2 or more.

Assuming that the filter output can be approximated by a Gaussian distribution, $Z(n)$ by Eq. (21) can be described as follows (see V. Poor and S. Verdu, "Probability of Error in MMSE Multiuser Detection," IEEE Trans. Information Theory., vol. IT-43, No. 3, pp. 858-871, May 1997).

$$Z(n)=\mu(n)b(n)+\eta(n) \qquad (22)$$

where $\mu(n)$ is an equivalent amplitude of the output signal and $\eta(n)$ represents a Gaussian distribution of an average 0 and the variance $v^2(n)$. Therefore, $\mu(n)$ and $v(n)$ can be expressed as follows:

$$\begin{aligned}\mu(n)&=E\{Z(n)b(n)\}\\&=[H_m(n)^H[H_m(n)\Lambda(n)H_m(n)^H+\sigma^2I]^{-1}H_m(n)]_{J,J} \qquad (23)\end{aligned}$$

where $[]_{J,J}$ indicates the element at the intersection of the J-th row and the J-th column of the matrix.

$$v^2=\mathrm{var}\{Z(n)\}=\mu(n)-\mu^2(n) \qquad (24)$$

From the above, the extrinsic information derived by the linear equalizer can be deduced from the following equation.

$$\lambda_1[b(n)]=\log\frac{p(Z(n)\,|\,b(n)=+1)}{p(Z(n)\,|\,b(n)=-1)}=\frac{4\mathrm{Real}\{Z(n)\}}{1-\mu(n)} \qquad (25)$$

To obtain the optimum tap coefficient $G(n)$ with the above-described method, however, it is necessary that the inverse matrix calculation expressed by the following equation be conducted in Eq. (20) for each point in time; hence, much time is required for calculation.

$$\Phi(n)=[H_m(n)\Lambda(n)H_m(n)^H+\sigma^2I]^{-1} \qquad (26)$$

With the conventional method for iterative equalization by the linear equalizer, the inverse matrix calculation needs to be conducted for each point in time to update the tap coefficient--this gives rise to the problem of high computational complexity.